电网数据分析

张天野

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1 暂态稳定性评估（TSA）

输入：暂态稳定数据。暂稳数据是通过仿真程序模拟计算得到，一份暂稳数据包含有多个样本，包括稳定与不稳定的情况。

备注：电网的整体稳定表现为在各个物理监视量上均是稳定的，包括电压稳定、频率稳定、功角稳定等。

1.1 稳定性判断

输出：判断给定的样本是否稳定。这里指的稳定可以是电网的整体稳定（各个物理量上），也可是单个物理量上。

已有方法：

- 二分类问题 (也有描述成预测的，但本质就是分类)：决策树、SVM [12]、神经网络等 [1]、集成学习多个分类器 [8]。
- 基于预测：预测值与实际值不符的样本为不稳定的 [9]。

1.2 特征选择

输出：用于解决问题 1.1的（重要）特征子集。

已有方法：基于随机森林的递归特征选择策略 [13]。

1.3 电力调度

输出：调度方案。

说明：低频减载（UFLS）问题就属于电力调度，通常事故起因是发电机退出导致网内供电低于负载，会导致频率不稳定。UFLS 就是在事故后提供新的电力调度方案，使得网内频率稳定的方案。UFLS 通常使用暂稳数据中的频率字段，因此分类到 section 1 中。

已有方法：神经网络 [10]、电力计算方法 [7]。

2 故障检测

输入：电网传感器数据。通常由网内的电压变压器上的传感器以电压信号的形式传输，研究时通常只考虑一段时间内的信号。

备注：故障检测通常分为三部分子内容，故障检测、定位与分类。实现故障检测的方法往往能同时完成此三种任务。通常的流程分为三步，信号处理、特征提取、模式识别。

已有方法：神经网络、支持向量机 [5]、聚类、统计模型等。详细可见综述 [2, 6]。

2.1 故障检测

输出：是否发生故障

2.2 故障定位

输出：故障的位置。

2.3 故障分类

输出：故障的类别。

3 配置设定

输入：电网拓扑结构、各个节点上各个控制变量的概率分布。

输出：各个节点上个控制变量限制范围。

常用方法：增强学习 [11, 3]。

备注：配置设定是为电网上的某些节点设定其上控制变量的变化限制，例如常见的 Load Flow 问题。大部分工作试图通过自动方法配置电网，使其能再孤岛模式下自发运转。

4 其他

上述的问题整理均是从我们的视角的出发，此外还有一些以电力专家视角发现的电力领域问题，例如安全稳定控制、自动发电控制、电压无功控制等 [14, 4]。

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Problem	Type of control	RL method	Reference(s)
Electricity market simulation	Market decision	Q-learning	Harp et al. (2000) Rahimiyan et al. (2010) Nanduri and Das (2007) Lincoln et al. (2012) Kim et al. (2016) Krause et al. (2006)
Transient angle instability	Emergency	Q-learning	Ernst et al. (2004) Glavic (2005) Glavic et al. (2005a) Glavic et al. (2005b) Li and Wu (1999)
		Fitted Q iteration	Ernst et al. (2009)
		Policy search	Mohagheghi et al. (2006)
Oscillatory angle instability	Emergency	Q-learning	Ernst et al. (2004) Wang et al. (2014) Glavic et al. (2005a) Ademoye and Feliachi (2012) Karimi et al. (2009)
Voltage control	Normal	Q-learning	Xu et al. (2012) Vlachogiannis et al. (2004)
AGC (Automatic) generation control)	Normal	$Q(\lambda)$ with elig. traces	Yu et al. (2011)
		Q-learning	Daneshfar and Bevrani (2010) Ahamed et al. (2002)
		$R(\lambda)$	Yu et al. (2012b)
Economic dispatch	Normal	Q-learning	Jasmin et al. (2011) Yu et al. (2016)
Wide-area control	Emergency	TD	Yousefian et al. (2016)
		Q-learning	Yan et al. (2016) Hadidi and Jeyasurya (2013)
Households control	Normal	Q-learning	Wang et al. (2016) Yan et al. (2016)
Wind generation control	Normal	Q-learning	Wei et al. (2015) Tang et al. (2015)
		$Q(\lambda)$	Yu et al. (2012a)
Demand control	Normal	Fitted Q iteration	Ruelens et al. (2016) Vandael et al. (2015)
System restoration	Restorative	Q-learning	Ye et al. (2011)
Congestion management	Emergency	Q-learning	Zarabbian et al. (2016)
Microgrids control	Normal	Q-learning	Khorramabady et al. (2015) Li et al. (2012)
		Policy search	Venayagamorthy et al. (2016)

图 1: 其他电力问题

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